Support Vector Machine based Classification into Groups using Discriminant Function

R. Viswanathan, Dr. K. Perumal,

Assistant Professor, Dept. of Information Technology and Management, Arul Anandar College, Karumathur,

Madurai, India

Associate Professor, Dept. of Computer Applications, Madurai Kamaraj University, Madurai, India

Abstract: Support Vector Machines(SVMs) support vector networks and also supervise learning models with associated learning algorithms that analyze data and recognize patterns used for classification and regression analysis. They implement the principle of structural risk minimization and have excellent generalization ability as a result, even when the data sample is small. The SVMs performs a classification tasks by constructing an optimal separating hyper plane that maximizes the margin between the two nearest data points belonging to two separate classes.The state of art of this work is based on the hippocampus shape and structure of the brain components. This framework works in three phases. In the first phase, extraction of shape and texture features from the image. In the second phase, hippocampus detection and its volume calculation are performed. In the third phase, the features are used to classify the groups using discriminant function analysis. The researcher uses Support Vector Machine to classify into groups. The main focus is to diagnosis the disease related to brain and Alzhimers Disease, and to identify the cerebral cortex of brain and the cavity area in sulci. The preliminary research results prove that the proposed architecture has high contribution to computer aided diagnosis of AD.

KEYWORDS: Support Vector Machine, Hippocampus, Alzheimer's disease, Medical imaging.

I. INTRODUCTION

The human brain is the center of the human nervous system and is the most complex organ in any creature on earth. Any abnormality in brain leads to the total collapse of entire vital functions of the body. This paper introduces a concept of simple user friendly GUI application to process an image of brain and analyze its morphological abnormalities.

II. PROBLEM DEFINITION

The old age patient and young patient are affected through AD. Here the typical abnormality of brain is in shrinking of its cerebral cortex region. The spaces in the folds of the brain are grossly enlarged. This type of abnormality leads to Alzheimer's disease. Here the major objective is to identify the cerebral cortex region of brain and measure the cavity area in sulci.

III. LITERATURE REVIEW

Goyal showed a technique for automatic detection of some types of brain abnormalities, along with techniques for tumor segmentation in MRI sequences. They presented an automated and clinically-tested method for detection of brain abnormalities and tumor-edema segmentation using MRI sequences. Their method follows a Radiologist's approach to the brain diagnosis using multiple MRI sequences instead of any prior models or training phases.

Lashkari introduced an automatic brain tumor detection method to increase the accuracy and yield, and decrease the diagnosis time. The goal in his work was to classify the tissues into two classes: normal and abnormal. *MR* images that were used in his work were images from normal and abnormal brain tissues. He tried to give clear description from brain tissues using *Zernike* Moments, Geometric Moment Invariants, energy, entropy, contrast and some other statistic features such as mean, median, variance, correlation between corresponding points, and values of maximum and minimum intensity. He used a feature selection method to reduce the feature space as well. His method used neural networks to do that classification. The purpose was to classify the brain tissues into normal and abnormal classes

automatically; which saves the radiologist time, and increases accuracy and yield of diagnosis.

Reddy showed an improvement to fuzzy clustering means (FCM). They introduced an earlier spatial constraint into FCM algorithm, in which the spatial information is encoded through mutual influences of neighboring positions. To detect the abnormalities of Brain MRI images, they used a new spatial FCM, and compared the results with k-means and FCM techniques.

Magnin used the relative weight of gray matter versus white matter and cerebrospinal fluid in 90 regions of interests (ROI) as features classified with SVM. Based on the bootstrap method, the SVM obtained 94.5% average classification accuracy in the classification of 16 AD and 22 control (healthy) subjects, with a mean specificity of 96.6% and a mean sensitivity of 91.5%.

Ramírez proposed a classification system for AD based on the partial least square (PLS) regression model for feature extraction (identification of discriminative voxels) and the random forest (RF) classifier. The PLS-RF system yielded accuracy, sensitivity, and specificity values of 96.9%, 100%, and 92.7%, respectively, after classifying 41 normal and 56 AD images using the leave-one-out cross-validation method.

IV. METHODOLOGY
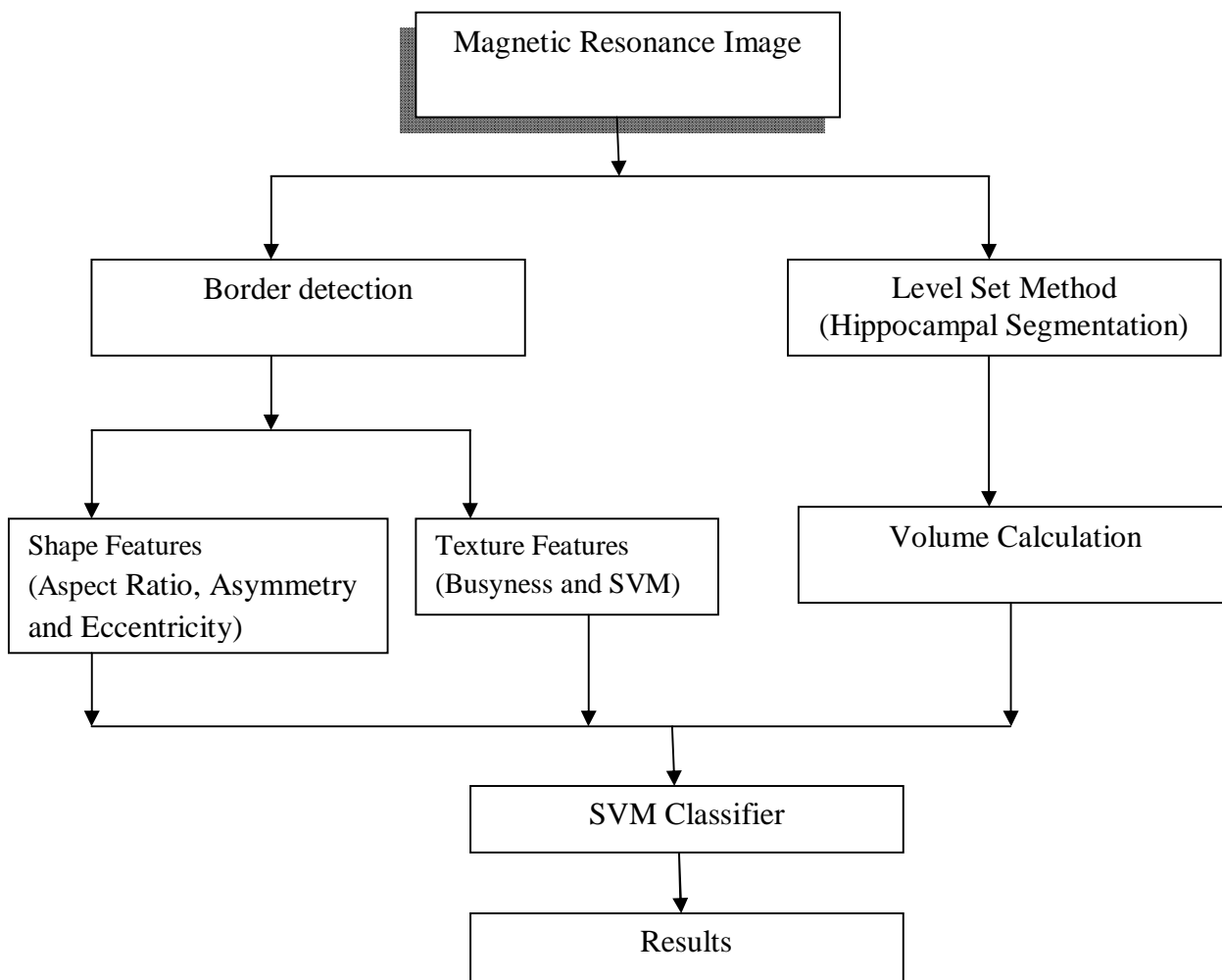
Data Flow Diagram for Detection and Volume Calculation using SVMs in AD

Level Set Method:

The level set method was used for hippocampus segmentation. The first step is used for computerized analysis for hippocampus size. The border structure of hippocampus provides vital information for its area. Here the asymmetry and border irregularity are calculated from the border. For border detection the level set method is used. The main advantage is implementation is consistent and no re-initialization is obtained. Faster curve evaluation is done, flexible and efficient initialization. The border detection method was applied to all slices and shows output result for border detection.

Shape Features:

Aspect ratio:

This can be defined as the ratio of length of major axis, L1, to the length of minor axis, L2. Here r0, c0 denotes the object of centroid and m_{pq} and μ_{pq} denote the (p + q) order geometric and central moments of the object.

$$m_{pq} = \sum_{i=0}^{rows} \sum_{j=0}^{cols} i^p j^q,$$

$$r_0, c_0 = \left(\frac{m_{10}}{m_{00}}, \frac{m_{01}}{m_{00}} \right),$$

$$\mu_{pq} = \sum_{i=0}^{rows} \sum_{j=0}^{cols} (i - r_0)^p \cdot (j - c_0)^q,$$

$$L_{1,2} = \left(8(\mu_{02} + \mu_{20} \pm ((\mu_{02} - \mu_{20})^2 + 4\mu_{11})^{\frac{1}{2}}) \right)^{\frac{1}{2}}$$

$$A_R = \frac{L1}{L2}$$

Asymmetry:

Asymmetry A1 and A2 is evaluated as follows: First major axis orientation is calculated. Second the object was rotated based n the central moment of object value to align the principal axes with the image x and y axes.

$$\theta = \frac{1}{2} \tan^{-1} \left(\frac{2\mu_{11}}{\mu_{20} - \mu_{02}} \right),$$

$$A_1 = \frac{\min(A_x, A_y)}{A} \times 100\%,$$

$$A_2 = \frac{A_x + A_y}{A} \times 100\%.$$

Eccentricity:

Here the object is defined as lines that intersect orthogonally at the centroid of object and represent the direction with zero cross correlation. The eccentricity is defined as

$$\varepsilon = \frac{(\mu_{02} - \mu_{20})^2 + 4\mu_{11}}{(\mu_{02} - \mu_{20})^2}.$$

Texture Feature

Busyness:

A busy texture is one in which there are rapid changes of intensities from one pixel to other pixel. The spatial frequency of intensity changes is very high. It reflects the level of busyness and magnitude of dynamic range of grey scale and contrast. The suppression of the contract aspect from the information about the spatial rate of changes in intensity indicates the degree of busyness of a texture. The busyness is represented as follows:

$$f_{bus} = \frac{\left[\sum_{i=0}^{G_h} P_i \, s(i) \right]}{\left[\sum_{i=0}^{G_h} \sum_{j=0}^{G_h} iP_i - jP_j \right]}, \; P_i \neq 0, P_j \neq 0,$$

The numerator is essentially a measure of the spatial rate of change in intensity and the denominator is the summation of the magnitude of difference between the different grey tone values. p_i is the probability of the occurrence of grey tone value I given by

$$P_i = \frac{N_i}{n^2}$$

SVM Classifier:

The support vector machine (SVM) classifier is based on statistical learning theory. It implements the principle of structural risk minimization and has excellent generalization ability as a result, even when the data sample is small. The SVM performs a classification tasks by constructing an optimal separating hyper plane that maximizes the margin between the two nearest data points belonging to two separate classes.

IV. HIPPOCAMPAL SHAPE

The hippocampus is a major component of the brains of humans and other vertebrates. Humans and other mammals have two hippocampi, one in each side of the brain. It belongs to the limbic system and plays important roles in the consolidation of information from short-term memory to long-term memory and spatial navigation. The hippocampus is located under the cerebral cortex; and in primates it is located in the medial temporal lobe, underneath the cortical surface. It contains two main interlocking parts: Ammon's horn and the dentate gyrus.
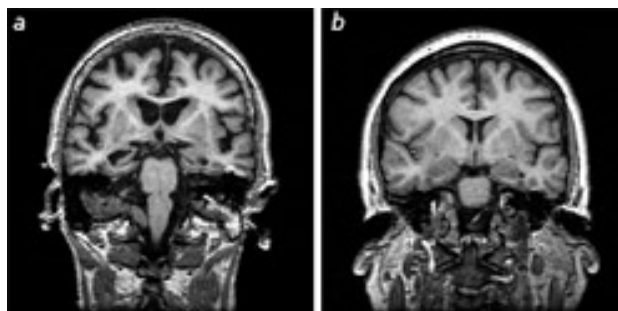
In Alzheimer's disease, the hippocampus is one of the first regions of the brain to suffer damage; memory loss and disorientation are included among the early symptoms. Damage to the hippocampus can also result from oxygen starvation (hypoxia), encephalitis, ormedial temporal lobe epilepsy. People with extensive, bilateral hippocampal damage may experience anterograde amnesia—the inability to form or retain new memories.

MRI scans offer a clearer and more detailed image of the brain and can show the difference between grey and white matter. The two main types of matter in the brain are grey matter, which forms the outer layer of the brain where information is processed, and white matter, which forms the inner core and provides the 'wiring' for information to move along. MRI scans are powerful enough to reveal subtle changes to the blood vessels in the white matter, a common sign of vascular dementia. Research has shown that MRI scans successfully reveal the loss of brain cells in the hippocampus in 80 to 90 per cent of cases of people with Alzheimer's disease, even in people who are in the early stages of the condition.

These images are MRI scans showing loss of cells from the hippocampus. a) Shows someone with Alzheimer's disease. b) Shows a control subject.

It is clear that people with Alzheimer's disease lose brain cells at a higher than normal rate. However, straightforward cell loss cannot be used to diagnose the condition as brain cells are also lost in other types of dementia. But a diagnosis can be made if scans can ascertain the pattern of loss. In Alzheimer's disease, the loss is usually greatest in the area responsible for memory, which is in the middle of the temporal lobe, whereas cell loss is more widespread and general in dementia with Lewy bodies and vascular dementia.

MRI scans can provide researchers with a useful tool for measuring the effects of anti-dementia drugs in clinical trials. Scans taken at two or three yearly intervals can provide information about the levels and location of cell loss over time, which would reveal valuable information about the positive effects of potential treatments.

V. SUPPORT VECTOR MACHINE

Support Vector Machines(SVMs) support vector networks and also supervise learning models with associated learning algorithms that analyze data and recognize patterns used for classification and regression analysis Given a set of training examples, each marked as belonging to one of two categories, an SVM algorithm builds a model that assigns new examples into one category or the other, making it a non-probabilistic binary linear classifier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible.

The support vector machine (SVM) classifier is based on statistical learning theory. It implements the principle of structural risk minimization and has excellent generalization ability as a result, even when the data sample is small. The SVM performs a classification tasks by constructing an optimal separating hyperplane that maximizes the margin between the two nearest data points belonging to two separate classes.

Hippocampal Segmentation:

The level set method was used for hippocampus segmentation. To analysis the computerized images hippocampus shape. The border structure of hippocampus provides vital information for its area.In this brain imaging the hippocampal segmentation is on the right ventricle on a affected brain with alzhimer (a) it shows the brain loss the functional lobe in which it measure for 16mm with high infected alzhimer disease, in second part (b) the brain is in normal healthy brain which is not affected by alzhimer.
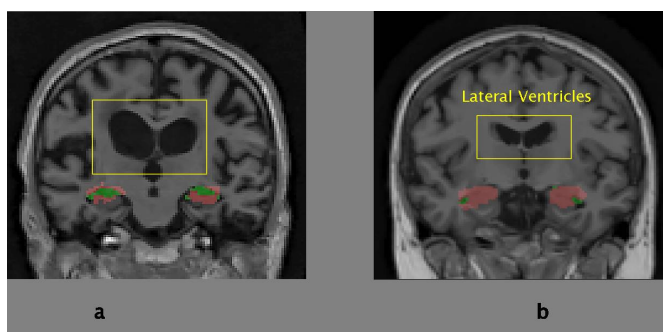
Volume Calculation:

Merely the volume were calculated by using hippocampus, the patient in India were affected by AD were about 150 million of people were in this disease. To support this volume to be calculated we were using support vector

machine with kernel algorithms to be detected. We were using this project to calculate the disease that was affected in mild, moderate and severe. For this purpose we were using this life time process to be calculated.

Hippocampus Volume Calculation for one patient with Alzheimer's disease;

No	Criteria	Alzhimers Disease	Controls	Significance
1	Age	82 (75 ^90)	7.000	P
2	Sex	Female (95%) Highly affected	5.000	-
3	Education	-	2.000	-
4	Hippocampus Volume	Right Ventricle – 90% Left Ventricle – 90%	8.000	P

Estimating the Life time risks were affected through Alzheimer's disease:
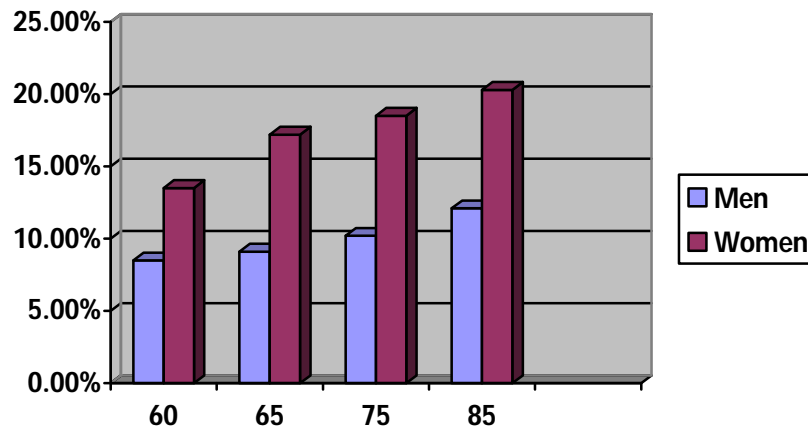
In Feature they can develop the tools and database for management and sharing of neuroscience data, and develop the tools for analyzing and modelling, and computational models of nervous system in Alzheimers disease. The main focus can be done in feature is , by using colour coding system, the measurement can be converted to metric form, the abnormality can be categorized by using Least Support Vector Machine and POS.

VI. RESULTS AND DISCUSSIONS

All classification results could have an error rate and on occasion will either fail to identify dementia or misclassify a normal patient as demented. It is common to describe the error rate by the terms of TP, TN, FP and FN. The Support Vector Machines use the feature extraction and volume of hippocampus for diagnosing and classifying the Alzhimers Disease. In this section the performance of proposed approach under fusion of feature extraction and hippocampus volume and a comparison with state of art methods of quantitative and qualitative performance is discussed.
Analysis:
The support vector machine yields to calculate the volume of hippocampus segmentation in various stages. The volume of hippocampus region and features vector is fed as input to Support Vector Machine. By using SVM it yields good accuracy to calculate and compare the hippocampus volume. The performance of proposed work is measured in terms of Sensitivity and Specificity. Here the sensitivity relates to the test of ability to identify positive result and specificity relates to identify negative results.
Sensitivity = Number of true positive / Number of true positive + Number of false negative
Specificity= Number of true negative / Number of true negative + Number of false positive

Volume of hippocampal region		
Test Images	Left Volume	Right Volume
1	0.1506	0.1587
2	0.1515	0.1593
3	0.1517	0.1584

VII. CONCLUSION

This paper proposed a hybrid support to diagnosis in Alzhimers Disease. The researcher found after analysing the MRI datasets of AD patients have reduced the content of grey matter, so it affect hippocampus region and morphological of brain. Therefore the volume of hippocampal segmentation is smaller in subject. To undergo this research, the researcher used hippocampus volume and feature extraction to detect by using Support Vector Machine.

REFERENCES

1. Chincarini, P. Bosco, P. Calvini et al., "Local MRI analysis approach in the diagnosis of early and prodromal Alzheimer's disease," NeuroImage, vol. 58, no. 2, pp. 469–480, 2011.
2. Magnin, L. Mesrob, S. Kinkingnéhun et al., "Support vector machine-based classification of Alzheimer's disease from whole-brain anatomical MRI," Neuroradiology, vol. 51, no. 2, pp. 73–83, 2009.
3. Bobinski M, de Leon MJ, Convit A, *et al*. MRI of entorhinal cortex in mild Alzheimer's disease. *Lancet*1999;353:38–40.
4. Convit A, de Asis J, de Leon MJ, *et al*. Atrophy of the medial occipitotemporal, inferior, and middle temporal gyri in non-demented elderly predict decline to Alzheimer's disease.*Neurobiol Aging*2000;21:19–26.
5. Salas-Gonzalez, J. M. Górriz, J. Ramírez et al., "Computer-aided diagnosis of Alzheimer's disease using support vector machines and classification trees," Physics in Medicine and Biology, vol. 55, no. 10, pp. 2807–2817, 2010.
6. Esiri MM, Pearson RC, Steele JE, *et al*. A quantitative study of the neurofibrillary tangles and the choline acetyltransferase activity in the cerebral cortex and the amygdala in Alzheimer's disease. *J Neurol Neurosurg Psychiatry*1990;53:161–5.
7. Fox NC, Freeborough PA. Brain atrophy progression measured from registered serial MRI: validation and application to Alzheimer's disease. *J Magn Reson Imaging*1997;7:1069–75.
8. G. Chen, B. D. Ward, C. Xie et al., "Classification of Alzheimer disease, mild cognitive impairment, and normal cognitive status with large-scale network analysis based on resting-state functional MR imaging," Radiology, vol. 259, no. 1, pp. 213–221, 2011.
9. Goyal, Soniya and Biswas. "Automatic Detection of Brain Abnormalities and Hippocampal Segmentation in MRI Sequences". Image and Vision Computing New Zealand Conference,IVCNZ 2011:NewZealand.
10. Imran MB, Kawashima R, Awata S, *et al*. Tc-99m HMPAO SPECT in the evaluation of Alzheimer's disease: correlation between neuropsychiatric evaluation and CBF images. *J Neurol Neurosurg Psychiatry*1999;66:228–32.
11. J. Ramírez, J. M. Górriz, F. Segovia et al., "Computer aided diagnosis system for the Alzheimer's disease based on partial least squares and random forest SPECT image classification," Neuroscience Letters, vol. 472, no. 2, pp. 99–103, 2010.
12. Jack CR Jr, Petersen RC, Xu YC, *et al*. Prediction of AD with MRI-based hippocampal volume in mild cognitive impairment. *Neurology*1999;52:1397–403.
13. Li, Lin; Wang, James Z.; Lozar, Carl; et al. Automated detection of mild cognitive impairment through mri data analysis, International Journal On Artificial Intelligence Tools Volume: 21 Issue: 5. Published: OCT 2012.
14. M. Graña, M. Termenon, A. Savio et al., "Computer aided diagnosis system for Alzheimer disease using brain diffusion tensor imaging features selected by Pearson's correlation," Neuroscience Letters, vol. 502, no. 3, pp. 225–229, 2011.
15. M. R. Daliri, "Automated diagnosis of Alzheimer disease using the scale-invariant feature transforms in magnetic resonance images," Journal of Medical Systems, vol. 36, no. 2, pp. 995–1000, 2012.
16. McKhann G, Drachman D, Folstein MF, *et al*. Clinical diagnosis of Alzheimer's disease: report of the NINCDS–ADRDA Work Group under the auspices of Department of Health and Human Services Task Force on Alzheimer's Disease. *Neurology*1984;34:939–44.
17. Meguro K, LeMestric C, Landeau B, *et al*. Relations between hypometabolism in the posterior association neocortex and hippocampal atrophy in Alzheimer's disease: a PET/MRI correlative study. *J Neurol Neurosurg Psychiatry*2001;71:315–21.
18. Ohnishi T, Matsuda H, Tabira T, *et al*. Changes in brain morphology in Alzheimer disease and normal ageing: is Alzheimer disease an exaggerated aging process? *AJNR Am J Neuroradiol*2001;22:1680–5.
19. R. Wolz, V. Julkunen, J. Koikkalainen, et al., "Multi-method analysis of MRI images in early diagnostics of Alzheimer's disease," Plos One, vol. 6, no. 10, Article ID e25446, 2011.